PLANT PESTS AND DISEASE DETECTION USING OPTICAL SENSORS

DALJINSKO ZAZNAVANJE RASTLINSKIH BOLEZNI IN ŠKODLJIVCEV

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ABSTRACT

Plant pests and disease detection using optical sensors

Traditional agricultural plant pest and disease management practices are based on visible characteristics and require that plants are checked individually, making these practices time consuming and therefore costly. Plant pests and diseases also often exhibit a heterogeneous distribution, making detection more difficult. Remote sensing methods enable comparatively accurate detection of pests and diseases over larger areas. Furthermore, because remote sensing sensors utilize light outside the human visible spectrum, presymptomatic detection becomes possible, thus facilitating timely, appropriate and spatially accurate management practices. Because remote sensing systems generate large amount of data, novel data analysis methods, such as machine learning, were introduced to plant protection. While pest and disease detection is possible using individual sensors, best results can be obtained by combining different sensors, utilizing different spectral ranges or physiological responses to light. A large amount of data and information has been generated in the past, but this research has mostly been focused on individual pathogens. Future research will have to focus on combined infections or infestations, and include abiotic stressors as well.

Key words: Remote sensing, plant protection, hyperspectral, multispectral, thermal, fluorescence, precision agriculture

IZVLEČEK

Daljinsko zaznavanje rastlinskih bolezni in škodljivcev

Velikokrat tradicionalni pristopi varstva rastlin pred rastlinskimi boleznimi in škodljivci temeljijo na vidnih simptomih, ki vključuje redno pregledovanje posameznih rastlin. Postopki so zato lahko dolgotrajni in s tem dragi. Bolezni in škodljivci imajo v prostoru pogosto heterogeno razporeditev, kar otežuje njihovo odkrivanje. Metode daljinskega zaznavanja omogočajo razmeroma natančno odkrivanje škodljivcev in bolezni na večjih območjih. Ker uporabljajo senzorji daljinskega zaznavanja tudi svetlobo izven nam vidnega spektra, je možno tudi zgodnje odkrivanje, t.j. odkrivanje pred razvojem vidnih znakov bolezni. To omogoča pravočasno, ustrezno in prostorsko natančno upravljanje z boleznimi in škodljivci. Sistemi daljinskega zaznavanja ustvarjajo velike količine podatkov, zato so bile v varstvo rastlin uvedene sodobne metode za analizo podatkov, na primer strojno učenje. Čeprav je možno zaznava bolezni in škodljivcev z uporabo posameznih senzorjev, lahko dosežemo najboljše rezultate z združevanjem različnih senzorjev, torej z uporabo različnih spektralnih območij ali fizioloških odzivov na svetlobo. Dosedanje raziskave so bile osredotočene na posamezne škodljivce in bolezni. Prihodnje raziskave se bodo morale osredotočiti na kombinirane okužbe ter vključevati tudi abiotske stresorje.

Ključne besede: daljinsko zaznavanje, varstvo rastlin, hiperspekter, multispekter, toplotno slikanje, fluorescenca, precizno kmetijstvo

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1 INTRODUCTION

Traditional agricultural management practices assume a homogenous distribution of plant pests and diseases in a field. But plant pests and diseases often exhibit a heterogeneous distribution, thus making traditional plant health management practices unsuitable to actual field conditions. Furthermore, traditional plant pests and diseases detection is based on visible characteristic symptoms of individual plants, and accuracy is further confounded by temporal variability of symptoms (Bock et al. 2008). Precision agriculture is a management system based on spatial and temporal variability in crop and soil factors within a field (Stafford 2000), and it utilizes various sensors and platforms to provide on-time and accurate mapping systems of crops, which facilitate timely and site-specific management decisions.

Given the heterogeneous distribution of plant pests and diseases, optical remote sensing techniques can be considered as a best-fit technology, providing information on disease foci, and infection and infestation severity (Gebbers and Adamchuck 2007, Mahlein 2016). Contemporary optical sensors generate comparatively large amounts of complex data, making remote sensing applications for plant protection an information and technology based domain. Advanced data analysis methods are crucial to effectively utilize remote sensing data for plant pest/disease detection. Regardless of the sensor and application, remote sensing data has to fulfil several criteria in order to be considered of adequate quality for plant pests or disease detection (Mahlein 2016). It has to enable: (1) early (i.e. presymptomatic) detection of pests and diseases, (2) differentiation of various pests and diseases, (3) discrimination between abiotic and biotic stress, and (4) quantification of disease or infestation severity. These criteria have to be assessed at least as accurately as with traditional methods, but with shorter computing times. Considering these requirements, machine learning methods are being increasingly employed for data analysis and detection method development (Behmann et al. 2014).

Remote sensing is the science of obtaining information about an object or area at a distance, without making physical contact with the object under study, by measuring the reflected or emitted radiation at a distance. Optical sensors utilize the light spectrum (Figure 1), both natural and artificial, from ultraviolet (wavelengths from 100 to 400 nm), to far infrared ($15*10^3$ nm to $350*10^3$ nm). Humans can perceive light in the so called visible range, from 400 to 700 nm. Near infrared (NIR) ranges from 700 to 1000 nm, and short-wave infrared from 1000 to 2500 nm (SWIR). Sensors above SWIR wavelengths are considered as pure infrared or thermal sensors, with varying spectral ranges. Light interacts with objects in three ways, reflection, transmission, and absorption (Lillesand 2004). In addition, as light passes through a medium, such as the atmosphere, it can hit suspended molecules and become scattered. The type and amount of scattering depends on particle size (e.g. particles smaller than the wavelength cause wavelength-dependant Rayleigh scattering, which predominantly scatters blue wavelengths, making the sky to appear blue), and has to be accounted for in remote sensing applications. Optical remote sensing sensors measure the combined effect of the main three phenomena (called spectral reflectance, often also referred to as reflectance), and their ratios at different wavelengths are characteristic for objects (e.g. plants, soil, and water), and enable their identification. This unique and characteristic combined reflectance is called spectral signature, i.e. spectral reflectance as a function of wavelength. The configuration of spectral signatures at various wavelengths depends on canopy optical properties, biophysical and biochemical attributes, illumination, background effects, and viewing geometry (Kupiec and Curran 1995).

Spectral signatures of plants are influenced by several factors, linked to specific areas of the light spectrum. In the visible part of the spectrum (400 – 700 nm), pigments are prevalent (e.g., chlorophyll, carotenoids, anthocyanins). In the near infrared region (NIR, 700 – 1000 nm), leaf morphology and structure influence signatures, while short-wave infrared (SWIR, 1000 – 2500 nm) reflectance is influenced by water and metabolites (e.g., cellulose and proteins) (Behman et al. 2014, Matese and Gennaro 2015) (Figure 1). Appropriate spectral analyses can detect these changes and can be used to characterize the plant's physiological state, and assess genotype-specific responses to biotic and abiotic stresses (Mahlein et al. 2012, Wahabzada et al. 2015).

2 OPTICAL SENSORS FOR PLANT PEST AND DISEASE DETECTION

Humans observe sunlight using two kinds of photoreceptors in the retina. Rod cells are sensitive to absolute light levels, and cone cells are used for colour vision. Cone cells come in three types (S-cones, M-cones, and L-cones), each more responsive to certain wavelength of visible light. S-cones are responsive to short-wavelength (blue) light, M-cones to medium-wavelength (green), and L-cones to long-wavelength (red) light. Humans perceive colour as a combination of these three spectral bands. This is also referred to as the

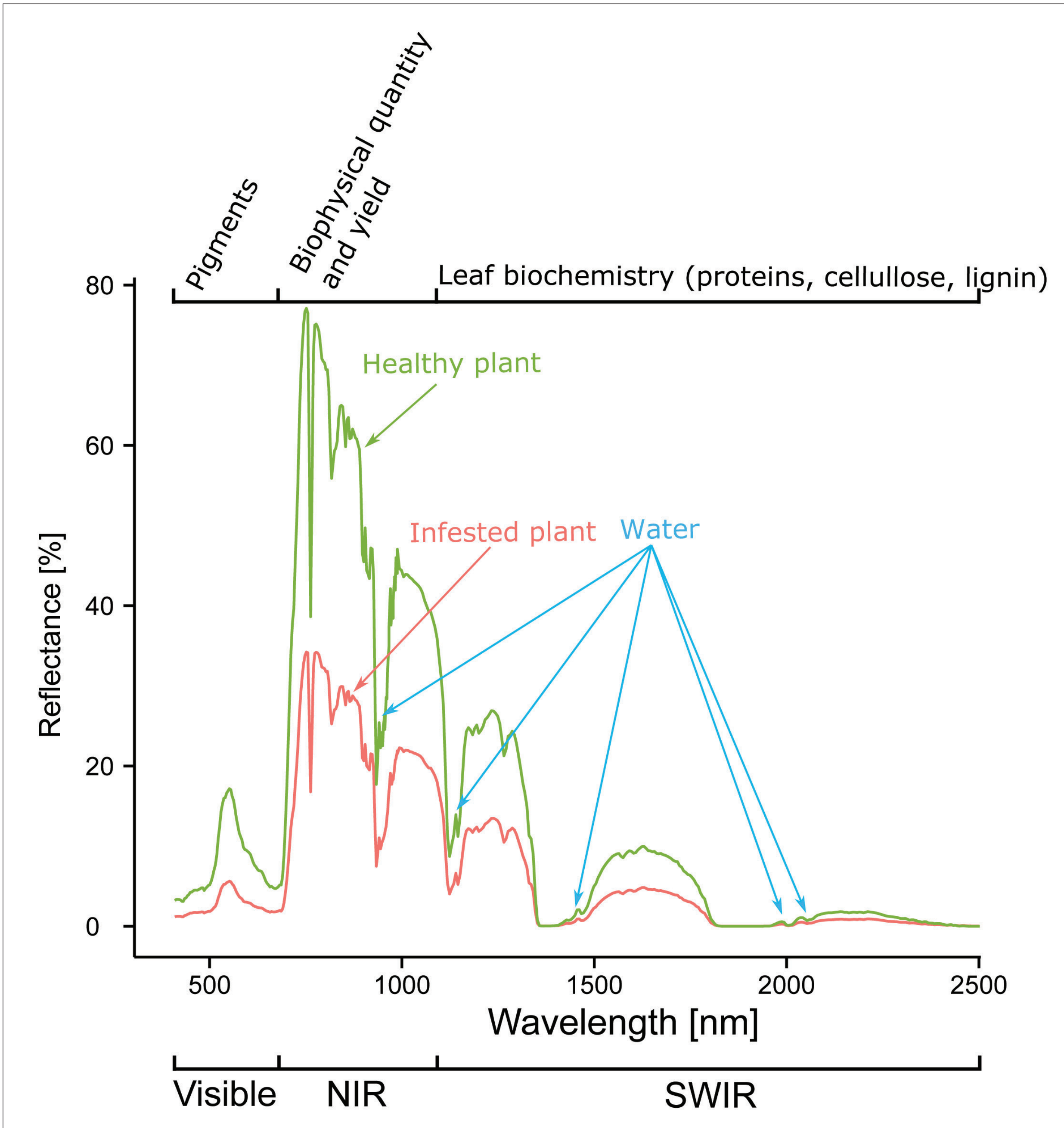

Figure 1: Spectral signatures of healthy and infested plants captured using a hyperspectral imaging sensor (Žibrat, unpublished data). Atmospheric water absorption bands can be observed, due to the high spectral resolution of hyperspectral sensors.

RGB colour system, which we use in electronic appliances (e.g. computer screens).

Optical sensors utilize the same system, by dividing the recorded light into spectral bands of various widths. Depending on the wavelength they record and the number of spectral bands they divide the light into, optical sensors can be classified into five groups: (1) RGB, (2) multispectral, (3) hyperspectral, (4) thermal, and (5) fluorescence imaging sensors. Regardless of the system, a standardized data acquisition step is of utmost importance in order to obtain results with high accuracy and repeatability. Low detection accuracy is often the result of low image quality (e.g. small spatial resolution) and heterogenic (e.g. non-uniform lighting) conditions.

2.1 RGB sensors

Standard, off-the-shelf digital cameras use the RGB (red-green-blue) system, and can be used for disease and pathogen detection. Because they are comparatively easy and cheap to produce, they have become ubiquitous, as almost everyone carries such a device on their mobile phone. RGB sensors can be used on various platforms, from hand-held to satellite mounted, providing information over large areas throughout the growing season.

RGB sensors have been used extensively for plant disease and pathogen detection. Neumann et al. (2014) used colour, gray levels, texture, dispersion, connectivity, and shape as features in pattern recoginition and machine learning schemes to detect cercospora leaf spot (*Cercospora beticola*), sugar beet rust (*Uromyces betae*), Ramularia leaf spot (*Ramularia beticola*), Phoma leaf spot (*Phoma betae*), and bacterial leaf spot (*Pseudomonas syringae* pv. *Aptata*) in sugar beet plants. Similarly, Bock et al. (2010) enhanced colour information with LAB (L – light, AB – colour-component dimensions), YCBCR (Y – luma component, CB – blue difference, CR – red difference chroma component), and HSV (Hue, Saturation, Value) information to detect Citrus canker (*Xanthomonas axonopodis*) in grapefruit. Texture-related features combined with support vector machines were used for detection of bacterial angular (*Xanthomonas campestris*) and ascochyta blight (*Ascochyta gossypii*) in cotton (Camargo and Smith 2009). Digital image analysis is well-established, and is also being applied in remote sensing of plant diseases and pathogens. Using the shareware software package Scion Image (Scion Corporation), Wijekoon et al. (2008) succesfully determined anthracnose (*Colletotrichum destrucivum*) infection severity (measured as percent diseased leaf area) in infected tobacco plants.

2.2 Multispectral sensors

Multispectral sensors utilize the RGB bands of visible light, and expand them into the NIR and SWIR spectral regions. Band width varies between sensors; generally shorter wavelengths (RGB) have narrower bandwidths than longer wavelengths (NIR and SWIR). Spatial resolution follows the same pattern. For example, the European Space Agency (ESA) satellite Sentinel-2 has a spatial resolution of 10 m in RGB bands, 10 – 20 m in NIR, and 20 – 60 m in SWIR. Off-the-shelf handheld, UAV-borne (unmanned aerial vehicle) and airborne sensors assess spectral information in up to ten bands. In addition to RGB, VNIR (visible to NIR), and SWIR regions, sensors aimed at agriculture also utilize the red-edge part of the spectrum. In this spectral area, between 700 and 750 nm, plant reflectance changes rapidly, from approximately 5 % to 50 %. Green plants absorb solar radiation in the photosynthetically active radiation (PAR) spectral region (400 – 700 nm), and reflect approximately half of incoming light in the near-infrared spectral region. Chlorophyll is almost transparent at wavelengths greater than 700 nm, while each cell acts as an elementary corner reflector (reflecting light directly back to the source). This effect is extensively used in vegetation indices.

Vegetation indices are spectral transformations of two or more spectral bands. They are designed to enhance vegetation properties and allow spatial and temporal comparisons of photosynthetic activity and canopy structure (Huete et al. 2000) (Table 1). These spectral indices can be classified into several groups, by various criteria: bandwidth (wide- and narrow-band indices), by number of bands (2 or more), calculation method (ratio or orthogonal), by objective (e.g. pigment indices), or historical development (first or second generation) (Bannari et al. 1995). One of the most well-known vegetation indices is the Normalized difference vegetation index – NDVI (Kriegler et al. 1969). NDVI is related to photosynthetic capacity and therefore to energy absorption of plant canopies (Myneni et al. 1995). In practice, NDVI has been used for a variety of purposes, e.g. in satellite imagery (Leon et al. 2012, Lanorte et al. 2014, Blaes et al. 2016).

Multispectral imaging has been used extensively in plant protection and health assessment research. For example, these types of sensors have been suc-

Table 1: Examples of broad- and narrow-band vegetation indices (adapted after Calderon et al. 2013 and references therein). In the "Abbreviation and calculation" column "Rn" refers to the reflectance measured at a wavelength of n nanometers.

Vegetation indices	**Abbreviation and calculation**
Structural indices	
Normalized difference vegetation index	$\mathrm{NDVI} = \frac{R_{800} - R_{670}}{R_{800} + R_{670}}$
Simple ratio	$\mathrm{SR} = \frac{R_{800}}{R_{670}}$
Modified simple ratio	$\mathrm{MSR} = \frac{\frac{R_{800}}{R_{670}} - 1}{(\frac{R_{800}}{R_{670}})^{0.5} + 1}$
Modified soil-adjusted vegetation index	$\mathrm{MSAVI} = \frac{2 * R_{800} + 1 - \sqrt{(2 * R_{800} + 1)^2 - 8 * (R_{800} - R_{670})}}{2}$
Modified triangular vegetation index 2	$\mathrm{MTVI2} = \frac{1.5 * (1.2 * (R_{800} - R_{550}) - 2.5 * (R_{670} - R_{550})}{\sqrt{(2 * R_{800} + 1)^2 - \left(6 * R_{800} - 5 * \sqrt{R_{670}}\right) - 0.5}}$
Modified chlorophyll absorption ratio index 2	$\mathrm{MSAVI2} = \frac{1.5 * (2.5 * (R_{800} - R_{670}) - 1.3 * (R_{800} - R_{550})}{\sqrt{(2 * R_{800} + 1)^2 - \left(6 * R_{800} - 5 * \sqrt{R_{670}}\right) - 0.5}}$
Pigment indices	
Transformed chlorophyll absorption in reflectance index	$\mathrm{TCARI} = 3 * (R_{700} - R_{670}) - 2 * (R_{700} - R_{550}) * \frac{R_{700}}{R_{670}}$
Normalized phaeophytinization index	$\mathrm{NPQI} = \frac{R_{415} - R_{735}}{R_{415} + R_{735}}$
Plant senescing reflectance index	$\mathrm{PSRI} = \frac{R_{680} - R_{500}}{R_{750}}$
Pigment specific normalized difference	$\mathrm{PSND}_c = \frac{R_{800} - R_{470}}{R_{800} + R_{470}}$
Photochemical reflectance indices	
Photochemical reflectance index (570)	$\mathrm{PRI}_{570} = \frac{R_{570} - R_{531}}{R_{570} + R_{531}}$
Photochemical reflectance index (670 and 570)	$\mathrm{PRI}_{m4} = \frac{R_{570} - R_{531} - R_{670}}{R_{570} + R_{531} + R_{670}}$
Normalized photochemical reflectance index	$\mathrm{PRI}_n = \frac{PRI_{570}}{\frac{R_{800} - R_{670}}{\sqrt{R_{800} + R_{670}}} * \frac{R_{700}}{R_{670}}}$

Chlorophyll fluorescence indices	
Reflectance curvature index	$\mathrm{LIC2} = \frac{R_{675} * R_{690}}{R_{683}^2}$
Colour indices	
Redness index	$\mathrm{R} = \frac{R_{700}}{R_{670}}$
Red/green index	$\mathrm{RGI} = \frac{R_{690}}{R_{550}}$
Lichtenthaler index	$\mathrm{LIC2} = \frac{R_{440}}{R_{690}}$
Plant disease indices	
Health index	$\mathrm{HI} = \frac{R_{534} - R_{698}}{R_{534} + R_{698}} - \frac{R_{704}}{2}$

cessfully used to detect panicle blast (*Magnaporthe grisea*) in rice (Kobayashi et al. 2001), greenbug (*Schizapis graminum*) infestations in wheat (Yang et al. 2005, 2009), citrus greasy spot disease in citrus (Du et al. 2008), late blight in tomato (Zhang et al. 2005), aphid (*Diuraphis noxia*) infestations in wheat fields (Backoulou et al. 2010), soybean cyst nematode (*Heterodera glycines*) (Nutter et al. 2002), streak mosaic virus in wheat fields (Mirik et al. 2011), head blight in winter wheat (Dammer et al. 2011), grapevine yellows (*Flavescence dorée*) in vineyards (Žibrat and Knapič 2015), and light leaf spot (*Pyrenopeziza brassicae*) in winter oilseed rape (*Brassica napus*) (Veys et al. 2018).

2.3 Hyperspectral sensors

Similarly to multispectral sensors, hyperspectral systems divide the spectrum in bands with a constant width of up to 10 nm, providing a much better spectral resolution. While multispectral vegetation indices can be used with hyperspectral data, and narrow-band indices have been developed (Marshall et al. 2016), the large amount of spectral data warrants the use of machine learning and neural networks for data analysis. Principal component analysis is often used as data exploration methods, and has been successfully used to monitor pathogenesis of *Fusarium graminearum* in wheat (Bauriegel et al. 2011). Supervised and non-supervised classification, clustering, self-organizing maps, and support vector machines have all been used for effective plant disease detection (Camargo and Smith 2009, Moshou et al. 2004, Rumpf et al. 2010). Even though a wide variety of methods have been tested, up to date none of them proved to be superior for all plant health assessment methods (Behmann et al. 2014).

In recent years, hyperspectral remote sensing has seen widespread use in plant protection. High spectral resolutions enable not only detection of abiotic and biotic stress, but also chemometric analyses, and identification of wavelengths related to infections and infestations, as well as early (i.e. presymptomatic) detection of infections or infestations (Susič et al. 2018, Zovko et al. 2019). Hyperspectral remote sensing has been used to quantify Rhizoctonia crown and root rot in sugar beet (Reynolds et al. 2012), *Venturia inaequalis* infections in apple (Delialieux et al. 2007), *Phytophthora infestans* in tomato (Wang et al. 2008), combined infections of Rhizoctonia and cyst nematodes (*H. schachtii*) in sugar beet (Hillnhütter et al. 2011), Fusarium head blight in wheat (Bauriegel et al. 2011), and differentiation between drought and biotic stress combined with presymptomatic detection of root-knot nematode (*Meloidogyne incognita*) infestations in tomato plants (Susič et al. 2018). The latter study led to development of hyperspectral remote sensing pre-processing and analysis guidelines (Žibrat et al. 2019). Furthermore, hyperspectral remote sensing is also used for screening fruits and crops to avoid storage disease. For example, Mehl et al. (2004) detected surface defects on apples, ElMasry et al. (2007) used hyperspectral imaging for detection of strawberry rot, and Qin et al. (2009) developed methods for detection of canker lesions of citrus fruits.

2.4 Thermal sensors

Infrared thermography assesses plant canopy temperature, which is correlated with plant stress and the microclimate in crop stands (Jones et al. 2002, Lenthe et al. 2007). But canopy temperature is also influenced by environmental factors, such as ambient temperature, sunlight, rainfall, and wind. Thermal detection methods therefore need to account for these confounding effects. Effective analyses consider the heterogeneity between and within leaves, i.e. the mean temperature difference within single leaves, plants, and crop stands has to be included. Systemic infections (e.g. *Fusarium* spp.) and root pathogens (e.g. *Rhizoctonia solani*) influence the transpiration rate and water flow of the entire plant or plant organs, leading to higher canopy temperatures. For example, Pinter et al. (1979) were among the first to find 3 – 4 °C higher canopy temperatures in diseased sugar beet and cotton plants. Similarly, Nilsson (1995) found that *Verticillium dahliae* infections caused a canopy temperature increase of 5 -8 °C in oilseed rape. Temperature changes were also observed for *Cercospora beticola* infections in sugar beet, and downy mildew (*Pseudoperonospora cubensis*) in cucumbers (Oerke et al. 2006). Oerke et al. (2011) managed to visualize the spatial spread of scab disease (*Venturia inaequalis*) on apples, and Gomez (2014) monitored *Peronospora sparsa* infections in *Rosa* varieties.

2.5 Fluorescence imaging

Fluorescence imaging (FI) commonly utilizes a LED or laser light source to assess photosynthetic electron transfer (Bauriegel et al. 2014), and photosynthetic activity can be measured by a variety of chlorophyll fluorescence parameters. For disease detection, the empirical fluorescence parameter Fv/F0 has been proposed for use on dark adapted plants (Kuckenberg et al. 2007). Fv/F0 is considered to be a representation of the maximum quantum yield of fluorescence (Buschmann et al. 1999), and has been used as an indicator of photosystem II (PSII) status and may estimate rates of energy transport from PSII to PSI in low-temperature fluorescence (–196 °C; Kitajima et al. 1975). Flourescence imaging requires plants to be prepared according to strict guidelines, and can therefore be challenging to implement in agricultural greenhouses or fields.

Nevertheless, FI is considered to be an effective tool for examining the development and effects of bacterial, fungal, and viral infections on leaves of cultivated plants (Daley 1995). Bürling et al. (2011) used FI to differentiate between nitrogen deficiency and powdery mildew in wheat. By combining FI and image analysis, Konanz et al. (2014) achieved successful discrimination and quantification of fungal infections and nitrogen deficiency in sugar beet, grapes, and barley. FI was also used to assess heat stress (Wang et al. 2011), nutrient deficiencies (Tartachnyk et al. 2006), leaf rust (Bürling et al. 2010), and leaf blotch (Robert et al. 2006). Early detection is also possible, for example leaf rust and powdery mildew infections on wheat leaves (Kuckenberg et al. 2007). Infections by *Pseudomonas syringae* in *Arabidopsis thaliana* can be detected a few hours after inoculation (Matous et al. 2006), while leaf rust and mildew on winter wheat could be detected merely a few days prior to development of visible symptoms (Kuckenberg et al. 2009).

3 FUTURE PERSPECTIVES

This review demonstrates the applicability of different optical remote sensing methods for detecting and differentiating abiotic and biotic stress in plants. Fluorescence imaging and thermography are sensitive to early stress responses in plants, but cannot identify specific diseases. The latter is possible using RGB, multi-, and hyperspectral sensors. A comparatively large amount of information regarding remote sensing of plant diseases and pathogens has been generated. The accumulation of large amounts of data has led to the introduction and development of novel analysis methods, such as machine learning and neural networks.

In order to become truly useable in field and greenhouse conditions, any novel remote sensing research should also focus on combined abiotic and biotic stress. Visible symptoms in the canopy are often similar, or possibly identical, and visual identification of individual plants doesn't yield satisfactory results. Remote sensing methods provide a good alternative, and can be adapted to different platforms. Furthermore, presymptomatic detection would facilitate precision agriculture and integrated pest management approaches at field and greenhouse levels, by enabling timely and accurate management practices. Furthermore, best results can be obtained by combining different sensors and advanced analysis methods, even though individual sensors can achieve comparatively good results.

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POVZETEK

Tradicionalne prakse zatiranja rastlinskih bolezni in škodljivcev predpostavljajo njihovo homogeno prostorsko razporeditev na poljih, vendar so bolezni in škodljivci v prostoru pogosto razporejeni heterogeno, Tradicionalni pristopi varstva rastlin velikokrat temeljijo na vidnih simptomih, za kar je potrebno redno pregledovanje posameznih rastlin. Postopki so zato lahko dolgotrajni in dragi. Natančno kmetijstvo je sistem upravljanja, ki temelji na zagotavljanju natančnih prostorskih in časovnih podatkov različnih rastnih dejavnikov ter razvoja in stanja rastlin. Pri tem uporablja različne senzorje z različnih platform, ki omogočajo pravočasno in prostorsko natančno ukrepanje.

Glede na heterogeno prostorsko porazdelitev rastlinskih škodljivcev in bolezni je daljinsko zaznavanje z optičnimi senzorji najprimernejša tehnologija, ki zagotavlja informacije o žariščih ter jakosti okužb. Napredne metode za analizo podatkov so ključne za učinkovito uporabo podatkov daljinskega zaznavanja za odkrivanje rastlinskih škodljivcev in bolezni. Ne glede na senzor in aplikacijo morajo podatki pridobljeni z daljinskim zaznavanjem izpolnjevati več meril, da jih lahko uporabljamo za določanje rastlinskih bolezni in škodljivcev. Omogočiti morajo: (1) zgodnje odkrivanje škodljivih organizmov in bolezni, (2) ločevanje različnih škodljivcev in bolezni, (3) ločiti morajo med abiotskim in biotičnim stresom in (4) kvantifikacijo bolezni ali jakosti okužbe. Ta merila morajo oceniti najmanj tako natančno kot s tradicionalnimi metodami, vendar s krajšimi časi obdelave podatkov. Glede na te zahteve vse pogosteje uporabljajmo metode strojnega učenja za analizo podatkov in razvoj metod za določevanje bolezni.

Daljinsko zaznavanje je znanost o pridobivanju informacij o predmetih ali območju na daljavo, brez fizičnega stika med senzorjem in predmetom, ki ga proučujemo. Optični senzorji izkoriščajo svetlobni spekter, tako naravnega kot umetnega, od ultravijoličnega (valovne dolžine od 100 do 400 nm) do dolgovalovne infrardeče svetlobe ($15 * 10^3$ nm do $350 * 10^3$ nm). Ljudje zaznavamo svetlobo v tako imenovanem vidnem razponu, od 400 do 700 nm. Bližnje-infrardeča svetloba (NIR) sega od 700 do 1000 nm in kratkovalovna infrardeča svetloba od 1000 do 2500 nm (SWIR). Čisti infrardeči oziroma toplotni senzorji zajemajo elektromagnetno sevanje pri večjih valovnih dolžinah kot so valovne dolžine v območju SWIR-a. Med predmeti in svetlobo so možne tri interkacije, odboj, presevanje in absorpcija. Ob prehodu skozi medije, kot je atmosfera, se svetloba sipa zaradi interakcij z molekulami. Vrsta in jakost sipanja sta odvisni od velikosti delcev (npr. delci manjši od valovne dolžine povzročajo Rayleighovo sipanje, ki je odvisno od valovne dolžine), kar moramo upoštevati pri metodah daljinskega zaznavanja. Optični senzorji merijo skupni učinek glavnih treh interakcij (t.i. spektralni odboj, ki se pogosto imenuje tudi odbojnost), njihova razmerja na različnih valovnih dolžinah pa so značilna za objekte (npr. rastline, tla in vodo) in omogočajo njihovo identifikacijo. Tej edinstveni in značilni odbojnosti pravimo spektralni podpis, t.j. spektralna odbojnost kot funkcija valovne dolžine. Spektralni podpisi so odvisni od optičnih lastnosti nadzemnih delov rastlin, biofizikalnih in biokemičnih lastnosti, osvetlitve, ozadja in geometrije med senzorjem in objektom.

Optične senzorje delimo na pet skupin: RGB, multispektralni, hiperspektralni, termalni in fluorescenčni senzorji. Čeprav je zaznavanje bolezni in škodljivcev možno s senzorji vseh petih skupin, je izbira senzorja odvisna od platforme (npr. v rastlinjaku, brezpilotni le-

talnik, letalo, satelit) in željene natančnosti. Na primer, RGB senzorji omogočajo določanje prisotnosti bolezni, ki povzročajo spremembe na listih, njihova uporabnost za določanje okužb pred razvojem vidnih simptomov pa je omejena. Slednje omogočajo multi- in hiperspektralni ter toplotni senzorji. Te štiri skupine senzorjev lahko tudi uporabljamo na večjih razdaljah (na primer na letalu), z naravno osvetlitvijo. Senzorji fluorescence omogočajo natančno določanje bolezni, vendar zahtevajo natančno pripravo vzorcev in ustrezno umetno osvetlitev. Zato so primerni za uporabo na omejenih površinah, na primer v rastlinjakih in laboratorijih.

Dosedanje raziskave daljinskega zaznavanja za določanje rastlinskih bolezni in škodljivcev so se osredotočale na posamezne bolezni. Bodoče raziskave daljinskega zaznavanja se bodo morale osredotočiti na mešane okužbe in kombinirane biotske in abiotske strese. Vidni znaki biotskih in abiotskih stresov so pogosto podobni, če ne celo povsem enaki, vizualna identifikacija posameznih rastlin pa pogosto ne daje zadovoljivih rezultatov. Metode daljinskega zaznavanja so dobra alternativa in jih je mogoče prilagoditi različnim platformam. Poleg tega omogočajo določanje stresorjev pred razvojem vidnih znakov, kar olajša natančno kmetovanje in integrirane varstvo rastlin. Čeprav lahko posamezni senzorji dosežejo zadovoljive rezultate, lahko z združevanjem različnih senzorjev in naprednih analiznih metod rezultate izboljšamo.

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